A method to assess the influence of individual player performance distribution on match outcome in team sports

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Abstract

This study developed a method to determine whether the distribution of individual player performances can be modelled to explain match outcome in team sports, using Australian Rules football as an example. Player-recorded values (converted to a percentage of team total) in 11 commonly-reported performance indicators were obtained for all regular season matches played during the 2014 Australian Football League season, with team totals also recorded. Multiple features relating to heuristically determined percentiles for each performance indicator were then extracted for each team and match, along with the outcome (Win/Loss). A generalised estimating equations model comprising eight key features was developed, explaining match outcome at a median accuracy of 63.9% accuracy under 10-fold cross validation. Lower 75th, 90th and 95th percentile values for team goals and higher 25th and 50th percentile values for disposals were linked with winning. Lower 95th and higher 25th percentile values for Inside 50's and Marks respectively were also important contributors. These results provide evidence supporting team strategies which aim to obtain an even spread of goal scorers in Australian Rules football. The method developed in this investigation could be used to quantify the importance of individual contributions to overall team performance in team sports.

Keywords: performance analysis, coaching, strategy, Australian Rules football

Introduction

In sport, the term 'performance indicator' is used to refer to an action variable that defines an aspect of a successful performance (Hughes & Bartlett, 2002). This definition has been used broadly to extend to anthropometric, physiological and skill-related variables (Reilly, 2001; Robertson, Burnett, Newton & Knight, 2012). In the team sport notational analysis literature, discrete performance indicators (i.e., passes completed, shots on goal) have specifically been used to develop models explaining competition outcome in football (Castellano, Casamichana & Lago, 2012), basketball (Gomez, Lorenzo, Barakat, Ortega & Palao, 2008) and rugby (Vaz, Van Rooyen & Sampaio, 2010). This information can then potentially be used to make inferences about which characteristics of competition are typically most important to achieving success.

However, such approaches have also experienced some criticism in the literature. Specifically, it has been proposed that they neglect to consider the spatiotemporal components of sporting competitions, such as the location and sequences of possession between multiple players (Cervone, D'Amour, Bornn & Goldsberry, 2014) and the dynamic, interdependent relationships that exist within a team (Clemente, Martins, Couceiro, Mendes & Figueiredo, 2014). Consequently, an increase in research relating to assessing player and ball movement patterns as they pertain to team performance has gained popularity of late (Cervone *et al.,* 2014; Clemente *et al.,* 2014; Passos, Davids, Araujo, Paz, Minguéns & Mendez, 2011). Additionally, investigations into quantifying the contribution of individual players within a team context have also emerged (Duch, Waitzman & Amaral, 2010; Tavana, Azizi, Azizi & Behzadian, 2013).

As in many professional team sports, the collection and reporting of performance indicators is commonplace by the 18 teams participating in the elite-level Australian Football League (AFL) competition. Australian Rules football is played on an oval field with two opposing teams consisting of 22 players each (18 on the field + 4 interchange).

Scoring is achieved by kicking the ball between the two large goal posts located at either end of this field. In the AFL, discrete performance indicators are typically obtained via a commercial sports statistics company (Champion Data Pty Ltd, Melbourne, Australia), which uses a mixture of live and retrospective video coding in order to produce data for both professional clubs and media sources. Investigations into how these performance indicators associate with match outcome, defined as either 'Win/Loss' (Robertson, Back & Bartlett, 2015; Stewart, Mitchell & Stavros, 2007) or score differential (Stewart, Mitchell & Stavros, 2007) have been previously undertaken. In these studies, higher team totals relative to the opposition for kicks, Inside 50's and goal conversion were shown to be particularly influential on the match result.

Recent improvements in the reporting combined with the technologies used to capture such information (i.e., wearable athlete devices) has seen a concurrent increase in both the number and complexity of performance indicators reported in the AFL. Attempts to quantify the individual's contribution to the team in the AFL have also been noted in both the media (i.e., the AFL player ranking system) and the peer-reviewed literature (Heasman, Berry, Dawson & Stewart, 2008; Sargent & Bedford, 2013). In addition to understanding the value of an individual to the team, these approaches may also allow for the evaluation of player selections for a given match.

However, it is evident that each team sport contains a unique set of constraints which limit the contribution of an individual player to the overall success of their team (Vilar, Araujo, Davids & Travassos, 2012). These constraints can be conceptualised as relating to the individual, task or environment and differ for each sporting competition (Newell, 1986). Examples include the position played (Bourbousson, Deschamps & Travassos, 2014), the physical and technical abilities of an individual (Kempton, Sirotic, Cameron & Coutts, 2014) and their designated role within the team (Buszard, Farrow & Kemp, 2013). In Australian Rules football specifically, given the percentage of match time typically spent by a defender in their own half of the field it may be unreasonable to expect this individual to create as many scoring opportunities as a forward player. In contrast, a defender may be expected to produce a higher contribution to the team total for tackles than a forward, due to their defined role within the team.

Despite these generally accepted perceptions, a quantitative method of understanding how the distribution of individual player contributions within a team relates to achieving a successful match outcome has not been reported in the literature to date. In basketball for example, it could be hypothesised whether it is preferable for a single player to record a high percentage of a team's points scored in a game, or whether a more even spread of contributors is desirable? Obtaining this type of information for performance indicators having previously been shown as important to match outcome in a sport would have clear practical benefits. Notably, such findings could be used to inform team selection (i.e., optimisation of team structure), improve the validity of player scouting and list/roster management as well as increased sophistication of existing performance analysis.

This study developed a method to assess the influence of the distribution of individual player contributions in team sport on match outcome. The aim of this study was to provide an application of this method using AFL performance indicator data obtained from all 18 teams during the 2014 regular season.

Methods

Data collection and analysis

Performance indicator data from all 198 games played during the 2014 AFL regular season was obtained from www.afl.com.au/stats. Specifically, a total of 13 discrete performance indicators were selected for extraction based on their reporting in previous literature (Robertson, Back & Bartlett, 2015; Stewart *et al.*, 2007; Tangalos, Robertson, Spittle &

Gastin, 2015; Young & Prior, 2007), with definitions of each presented in Table I. The study was approved by the relevant human research ethics advisory group.

****INSERT TABLE I ABOUT HERE****

Following this, raw (absolute) individual player (*n* = 22) values for each performance indicator (*n* = 13) were extracted for all AFL teams (*n* = 18). This process was undertaken for all 22 games each team played during the 2014 regular season (*n* = 396), with the match outcome (Win/Loss) also obtained. One draw occurred during the 2014 season; this match was removed from the analyses. As all 22 player contributions for each team were included in the dataset, the sample consisted of players injured during the course of a match, along with a single substitute (a player who typically only participates in one quarter of a match).

Coding reliability and validity

As performance indicator data is provided to the AFL by a commercial provider (Champion Data Pty Ltd, Melbourne, Australia), the reliability and validity of such information is not publicly available. In order to determine the inter-rater reliability of the extracted data, a sample of all matches from a single round during the 2014 AFL season were selected for assessment. This process consisted of the lead author observationally coding each of the nine matches for all 13 performance indicators whilst blinded to the original AFL values. The coding was undertaken using a specially constructed output window in Sportscode (version 10.3, Sportstec Pty Ltd, Warriewood, Australia). Three time-synchronised video files for each match (side, behind the goals and broadcast view) were used to undertake the coding, with all vision provided by a single AFL club. Totals of each performance indicator for all teams were then obtained and recorded for comparison with the AFL data. Kappa statistics were not able to be determined due to the research team being blinded to the original coding results from Champion Data. This meant that a direct comparison between raters may not have always resulted in the identical number of observations (i.e., a kick may be missed altogether by a coder, rather than misclassified as in typical scenarios where kappa or weighted kappa may be applied). Thus, using team totals (n = 18) for each performance indicator (n = 13), two-way mixed single measure intra-class correlation coefficients (ICC 3,1) were used to determine the agreement between AFL and author-coded values. To determine the validity of the author's coding, root mean square error (RMSE) values were obtained for each performance indicator in order to provide an absolute error estimate (using the AFL data as the criterion measure).

Data conversion and feature extraction

For modelling purposes, each of the 22 player's contribution to the team total was converted to its relative format, by transforming this value to a percentage of their team total for a given match. For example, if a team recorded a total of 200 kicks in a match and a player contributed 13 to this total, then this player's relative contribution to the team was calculated as 6.5%. This descriptive conversion process of data from an absolute to relative format (Ofoghi, Zeleznikow, MacMahon & Raab, 2013) allowed for multiple matches to be included in the modelling process, as different team totals for each performance indicator were anticipated for each game.

By descriptively converting data for all 22 players in a match, multiple features could then be extracted to provide a representative profile of each performance indicator for a given team. For instance, consider 'kicks' as the performance indicator of interest and the total number of kicks recorded in a game be M between m players. Let m_i be the number of kicks recorded by ith (i=1,2,…m) player. Define the weight of the ith player w_i as [m_i/M]. The profile of the team for kicks can then be quantified by m dimensional vector w=($w_{(1)}$,$w_{(2)}$,..,$w_{(m)}$). From vector w we can extract the features of the kick profile for the team by obtaining percentiles at levels being set at (0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95) respectively. The levels of the percentiles chosen for use in the study were selected heuristically. Therefore, the 11 features extracted for each performance indicator consisted of the minimum, maximum, mean, standard deviation as well as each of the abovementioned seven percentile levels. This meant that 143 features in total (11 features x 13 performance indicator) were extracted for each game played by each team. All features were then propagated forward for modelling, subject to validity screening. Following this, the ordered weight vector was then constructed for each performance indicator and match, with the corresponding features extracted for subsequent modelling. The complete information extracted in this manner was then collated along with match outcome (Win/Loss) and team identity.

Statistical Analysis

The method of generalized estimating equations (GEE) (Halekoh, Hojsgaard & Yan, 2006) was employed to construct a model explaining match outcome as a function of the feature set for the performance indicators. For the analysis, the family was set as binomial with an exchangeable correlation structure. Considered as an extension of the generalised linear model, GEE has recently shown increased use in sporting contexts (see van Ark *et al.*, 2015; Robertson, Burnett & Gupta, 2014; Young *et al.*, 2015 for examples). It is particularly useful in situations where longitudinal data are being considered, as many similar modelling techniques do not take into account the correlations between repeated measures on the same participants or group (Zeger, Liang & Albert, 1988; Ziegler & Vens, 2010). Further, GEE has been shown to show higher classification accuracy in comparison to methods such as logistic regression in such instances (Önder, 2015). In this study, the GEE method was used to explain the relationship between the match outcome and the corresponding feature set, whilst adjusting for the dependence of the 18 teams.

For the validity screening of predictors, only those features showing significantly different (P <0.05) means for match outcome (via ANOVA and not exhibiting a multi-collinearity problem (r = <0.80 with another feature) were included in the model. The parsimonious model was selected using the backward search method. The match outcome of win was set at predicted probability level of 0.7, due to overall classification performance being higher comparative to iterations using alternate levels (i.e., 0.5 = 56.3% and 0.6 = 58.1%). The proposed model was then evaluated by computing the overall accuracy for match outcome via 10 fold cross-validation for a random selection of 33% of the data. Analyses were undertaken using R (version 3.0.1, R Core Team, Australia) using the *Geepack* package (Yan, Højsgaard, & Halekoh, 2012).

Results

The reliability assessment revealed very high agreement between the author's and Champion Data's coding (ICC range = 0.947 to 1.000) for all performance indicators used in the study (Table II). Validity results showed low absolute error for the author's coding with respect to the Champion Data values (RMSE range = 0.0 to 4.5) Consequently, AFL reported values were used in all subsequent analyses.

**** INSERT TABLE II ABOUT HERE****

The validity screening resulted in the removal of 107 of the 143 features initially extracted, leaving 36 for inclusion in the modelling process. This feature set was further reduced to eight features based on each providing a significant (P <0.05) contribution to the GEE model.

****INSERT TABLE III ABOUT HERE****

Table III provides an overview of the contribution of the eight features to the model, based on their model estimate, standard error and corresponding Wald statistic. The three features providing strongest contributions to the model all related to the performance indicator Goals, with lower P_{75}, P_{90} and P_{95} values all most strongly linked with a winning team outcome. Lower P_{90} for Behinds and P_{95} values for Inside 50's were also positive contributors to the model. In contrast, higher P_{25} and P_{50} values for Disposals and P_{25} for

Marks were related with winning (Table III). Overall classification accuracy of the model (median ± SD) was reported at 63.9 ± 4.2% for the 10 fold cross-validation.

**** INSERT FIGURE 1 HERE ****

The individual influence of each feature on match outcome is presented in the Tornado plot shown in Figure 1. Each bar in the graph indicates the influence of the feature value when keeping all other variables constant (at their mean level) in the GEE model. The bars in blue represents the win probability for the lowest realised value of the feature for 2014, while the red bar relates to the win probability for highest realised value of the feature in the sample. Using Goals.P_{75} as an example, it can be seen that the probability of win is reduced from 83.84% to 18.94% as relative goal contributions to the team total decrease from the highest observed value to the lowest. Considering that the outcome of win is set at a probability level of 0.7 (or 70%), this example illustrates that lower P_{75} team values are preferable in order to maximise the probability of winning. In contrast, Figure 1 shows that for the feature Disposals.P25, the probability of win is improved from 5.99% to 72.64% as team relative disposal contributions increase from the lowest observed value to the highest.

**** INSERT FIGURE 2 ABOUT HERE ****

Figure 2 presents an example of the vector *w* for a win and loss scenario, in this instance for the performance indicator Goals. Figure 2a depicts the raw mean distribution of goals for each player in the 2014 AFL season, prior to conversion to a relative format. The *y* axis relates to the mean goals contribution per match, whilst the 22 players are represented on the *x* axis ordered by magnitude of their contribution. Unsurprisingly, winning teams displayed higher mean values for goals for all 22 players in the season. Specifically, Figure 2a shows that the leading individual player for winning teams contributed almost four goals per game to the team, whereas this value was less than three for losing sides. The figure also shows that a greater number of players typically contributed to the number of goals kicked for winning sides. Specifically, Figure 2b reveals the same data shown in Figure 2a, having been converted to relative values for each player (i.e., percentage contribution to team total). As is shown in the area curve, higher relative contributions to the team goal total is noted for the top six players for losing teams. This reflects the findings from the GEE model showing that lower P_{75}, P_{95} and P_{90} values are advantageous. In contrast, the tail of the Win curve is larger comparatively to that of the Loss, showing the importance of having greater contributions to team goals from multiple players. Specifically, it can be noted that during the 2014 season winning teams recorded up to 13 goal scorers, whereas this value was rarely higher than 10 for losing sides (Figure 2b).

**** INSERT FIGURE 3 ABOUT HERE ****

Figure 3 shows an example of the strongest feature of the model, Goals.P75, with respect to its mean value for each of the 18 AFL teams in both wins and losses. The sides have been ranked from left to right based on their final ladder position at the end of the regular season. With the exception of one team (Melbourne) Goals. P75 values were typically lower in losses compared to wins, further emphasising the generalisability of this particular feature's influence.

Discussion

This study aimed to develop a method of quantifying relative contributions from each of the 22 players on an AFL team, with respect to the influence on winning a match. To achieve this aim, each player's individual contribution was measured using 13 commonly-reported performance indicators, with the data then converted to a relative format and expressed as a percentage of the team total. Multiple features were then extracted from each performance indicator in this relative format, in order to represent the distributions across the 22 players in a team.

Results showed that only eight of the 143 extracted features contributed meaningfully to a model capable of explaining match outcome in the AFL. In particular, features relating to Goals and Disposals were prominent, with both providing multiple estimates to the model in the negative and positive direction respectively. Based on these estimates, it is apparent that players capable of playing both midfield and forward roles respectively should be considered by coaches when undertaking team selection. Specifically, the proposed model suggests that a comparatively more even contribution of individual goal scorers is beneficial to team success, whilst higher median (P_{50}) player disposal contributions are desirable. Given the three strongest features included in the model all related to the performance indicator Goals, it can be surmised that AFL sides should look to select a team capable of producing multiple goal kickers. In Australian Rules football typically six forwards will compete on the ground at any given time, along with same number of midfielders and defenders (18 in total). However, these results illustrate the importance of players other than forwards contributing to team goal scoring, particularly for winning sides.

This paper also provides a new insight into the manner in which performance indicator distributions across a team can be understood in order to maximise the likelihood of winning. Practically, team scouts, recruiting staff and list managers may use such information in order to identify potential deficiencies within their playing roster. Specifically, the findings relating to goal distribution potentially point to a need for the development of empirical position-specific models for Australian football, which have been previously considered as important to define in sport (Reilly, 2001). Specifically, it may be pertinent for list managers and coaches to compare the relative contributions from different positional groups based on match outcome or when competing against different opponents. This could then allow these staff to make more informed decisions relating to the type of player which should be recruited to their particular club, potentially maximising considerable time and financial investment in the process. It may also further inform the structure of team training, to focus on player and ball movement patterns which facilitate achieving these player contribution distributions. Based on the findings from this study specifically, it is clear that sides should look to practice situations which readily facilitate opportunities for a wide range of players to contribute to team scoring.

It should be noted that the GEE model proposed in this paper represents a population-averaged approach to addressing the question of explaining team sport match outcome. Although recent work has used the GEE method successfully for various purposes in both team and individual sports (van Ark *et al.,* 2015; Robertson, Gupta, Kremer & Burnett, 2014; Young *et al.,* 2015), the overall model performance in the present study could be considered as only fair. Specifically, just under two thirds of matches from the 2014 AFL were correctly classified. However, considering that the model takes into account only the differences in player performance distribution for winning and losing matches and not the magnitude (i.e., raw values), the results are nonetheless encouraging. Consequently, the methodology proposed could be implemented in a variety of team sports, particularly those with a similar number of players competing as in Australian football (i.e., rugby or football).

A limitation relating to this study was the lack of inter- and intra-rater reliability as well as validity data available for each of the performance indicators used. However, results from the comparison with our own analysis of a subset of data revealed generally high agreement for each performance indicator along with corresponding low RMSE values. The process undertaken by the commercial provider used by the AFL involves numerous human statistical coders working on multiple matches in a given week. Whilst previous research has also reported the validity of this data as high (O'Shaughnessy, 2006), unfortunately the inter- and intra-rater reliability of this information is not available. It is also possible that the addition of more sophisticated performance indicators currently used by AFL clubs (i.e., metres gained) or those from other domains (i.e., physical performance) may have improved the accuracy of the GEE model. Further studies could look to include the team distribution of high intensity running or the total distance covered by players. It may also be of interest to determine the success of this analysis approach in sports which include fewer players on the field at any one time.

Future work may look to undertake investigation into the external validity of this model by evaluating its performance on new data obtained over subsequent seasons. Specifically, it may be of interest to determine whether similar player contribution distributions have been associated with winning in previous years. Obtaining such information would serve to further elucidate any longitudinal changes in the game (see Norton, Craig & Olds, 1999 for previous work in this area). For instance, it would be beneficial to determine whether previous successful sides were more or less reliant on forwards providing the majority of scoring, or midfielders providing the majority of disposals. Further, the use of an alternative dependent variable in the modelling (i.e., score margin) may also yield different results and presents another future avenue for investigation. The use of machine learning analysis approaches may represent an alternative option to GEE in being able to identify multiple player performance distribution profiles for different teams. However, it is important to recognise that such analysis techniques do not adjust their output based on the level of correlation between multiple same-team performances which would likely be present in a sample typical of that used here. Nonetheless, these types of analyses may hold value in identifying non-linearity in the performance behaviour both between and within different teams and thus may have future applicability.

Conclusions

The findings of this study represent a novel approach to understanding the relative contributions of individual players in team sports with respect to match outcome. By extracting features relating to performance indicators in sport, a more thorough understanding of how different players contribute to a team’s success can be achieved. The accuracy of the model proposed in this study could potentially be further improved in future through the addition of data from previous AFL seasons, along with the inclusion of more sophisticated team performance indicators. Future work should focus on the application and refinement of this model to other team sports.

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Figure 1. Tornado plot displaying predicted probabilities of match outcome for each of the eight key performance indicator features in isolation when all others are held constant. The blue bars represent the probability of 'Win' when the feature is at the lowest level whereas the red bars represent the highest level

Figure 2. Mean (± SD) player contribution to team match totals for the performance indicator 'Goals' for games played during the 2014 AFL regular season. Figure 2a displays the contribution in absolute terms (raw), whilst Figure 2b displays the contributions as a percentage of the team total (relative)

Figure 3. Goals.P75 values for each of the 18 AFL teams represented by wins and losses in the 2014 regular season. Teams are ranked from left to right based on final ladder position at the end of the regular season